DETECTION OF HYPOVOLEMIA USING SHORT-TIME FOURIER TRANSFORM ANALYSIS OF S1 HEART SOUNDS

Wensheng Fan *Dana H. Brooks*

CDSP Center, ECE Department
Northeastern University, Boston, MA

J. Mandel, I. Calalang and J. H. Philip

Department of Anesthesia
Brigham and Women's Hospital, Boston, MA

ABSTRACT

In this paper we present preliminary findings from applying the short-time spectral analysis to intra-operatively recorded heart sound signals. The goal is to detect hypovolemia as revealed by changes in the S1 and S4 heart sound. We present a statistic based on the temporal distribution of energy bursts as a candidate classification feature.

1. INTRODUCTION

One of the difficult unsolved problems in anesthesia monitoring is the detection of hypovolemia [1]. Although markers such as blood pressure and heart rate are reliable in the awake patient, anesthesia confuses and delays this picture. Thus it is of interest to find hypovolemia indicators which respond quickly and can be monitored reasonably non-invasively. Heart sounds early in systole (S1 and S4) are sensitive to changes in blood volume in the heart chambers [2]. Thus, the purpose of this study is to investigate whether changes in acoustically monitored heart sounds during anesthesia can be used to detect hypovolemia.

Based on clinical observations made by one of the authors using electronic stethescopes, an observation was made that these sounds are modulated by respiration. A possible mechanism is decreased pulmonary venous return during inspiration due to the increased intra-thoracic pressure. The particular nature of the change in heart sounds which was observed clinically was the frequent presence of an S4-like gallup or a splitting of the S1 sound during expiration when intravascular volume was normal, and the absence of these same sounds when intravasular volume dropped.

Thus the hypotheses to be investigated are

1. Systematic change in S1 and/or S4 sounds can be detected during intra-operative hypovolemia.
2. This change in S1 and/or S4 can be detected more reliably during expiration than during inspiration.

Based on observations of recorded data and timing comparison to simultaneous ECG, we decided to concentrate first on changes in S1. These changes, although audible to human listeners, are difficult to observe visually in the acoustic waveform. We desired an analysis method which would mimic, at least to a first approximation, the performance of the human auditory system in this regard, in particular by maintaining temporal resolution at the cost of poor spectral resolution. This engineering characterization led us to using short-time spectral techniques. In this paper we describe the use of the Short-Time Fourier Transform (STFT) [3] to represent S1 sounds, and the use of signal processing methods to extract detection statistics from the modulus of the STFT.

2. METHODS

STFT: The STFT combines traditional time domain and frequency domain concepts into a single time-frequency framework. With the STFT one can characterize some time-dependent frequency changes [3]. We apply it here to detect changes in the temporal behavior of acoustic energy in the frequency interval appropriate for S1.

The discrete-time STFT of a signal $\mathbf{x(n)}$ at time segment l is given by

$$X(l,k) \triangleq X(lL/2,k) = \sum_{n=-\infty}^{\infty} x(n)w(lL/2-n)e^{-\frac{j2\pi nk}{L}}.$$

The sequence $x(n)w(lL/2-n)$ is a short-time interval of $x(n)$ at time interval index l whose length **L** is the width of the analysis window $w(n)$. Thus $w(lL/2-n)$ selects a particular interval of $x(n)$, centered around time instant $lL/2$, whose Discrete Fourier Transform (DFT) is $X(l,k)$. By placing the window every $L/2$ samples we overlap the windows by 50% to temporally smooth the transform, and we zero-pad the resulting signal before the DFT to frequency-smooth (or interpolate) it. After calculating the STFT, we have a temporally ordered series of short-time frequency-domain characterizations of $x(n)$.

Band-Limited Energy Signal: Based on our hypotheses we expect the audible changes in S1 to be reflected in differences in the temporal behavior of the short-time energy content in the bandwidth of S1 and S4. Moreover the short-time nature of our STFT (small L) implies poor spectral resolution, so only frequency-averaged quantities can be reliably estimated. Since S1 and S4 normally have most of their energy below 200Hz, we next calculate a band-limited energy signal, denoted **BES(l)**, at short-time interval l, as

$$BES(l) = \sum_{k=i_1}^{i_2} |X(l,k)|^2,$$

where $[i_1, i_2]$ are the frequency indices corresponding to 20 and 200 Hz. respectively.

Thresholding in amplitude: Again based upon the observed audible changes, our major goal is to detect the

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extent of a "split" sound in S1. To objectively detect this "split", our strategy is to first *quantize* the signal in amplitude, *i.e.* as either "on" or "off", and then to study the resulting pulse train. Thus we next generate a quantized pulse train signal, $QPT(l)$, from $BES(l)$, by means of a threshold. In our method, we determine the threshold as $\mathrm{T(BES)} = \mathrm{mean(BES)} + \mathrm{M} \cdot \mathrm{std(BES)}$, where std denotes standard deviation and the mean and standard deviation are taken over the length of $BES(l)$ for a particular S1 sound. Thus we have $QPT(l) = 1$ if $BES(l) \geq T$ and $QPT(l) = 0$ if $BES(l) < T$.

Classification statistic based upon interpulse interval distribution: After obtaining the QPT signal for each heart sound, we have transformed a noisy S1 waveform to an energy-based signal which estimates when the sound is "on" and when it is "off". If a heart sound is more split, it will tend in general to include some longer interpulse intervals. Thus we need to characterize the degree to which a given heart sound has distinct well-separated pulses, reflecting a split sound, or a more concentrated set of pulses, reflecting a sound which is not heard as being split. One way we have developed to characterize this behavior is to compute a histogram of the *intervals* between the pulses in a given S1 sound. The greater the extent to which there are longer inter-pulse intervals, the more "split" we consider the sound; sounds which are characterized by a QPT signal with no internal off intervals are considered to have an interpulse interval of 0.

Thus, our method can be summarized in four steps

$$Waveform \rightarrow STFT \rightarrow BES \rightarrow QPT \rightarrow Classification$$

3. RESULTS AND DISCUSSION

Experiment Setup: We report here a test of the above scheme on the data recorded with a *LifeSound* esophogeal transducer during anesthetic procedures at Brigham and Women's Hospital. At the beginning of the procedure the patient was normovolemic. Clinical signs of hypovolemia were observed during the procedure, after which fluid was infused and the patient returned to a normovolemic status. Data was recorded during all three phases. We recorded 20s epochs of heart sounds, ECG, and respiratory pressure simultaneously, at a sampling rate of 5 kHz. We manually identified 1024 point intervals (about .2 s) containing S1 sounds during expiration for analysis. We used $L = 64$ (12 msec intervals) in the STFT and set $M = 1$ in the threshold procedure.

Results: Fig. 1 illustrates typical results of this analysis. The first column in Fig. 1 shows the temporal S1 waveform. The second column shows the corresponding STFT, with time segment l on the horizontal axis and the frequency axis oriented into the plane of the page, and the third column shows BES (dotted line) and QPT (solid line). The QPT signals have been scaled in amplitude for illustration. We observe that the change in S1 characteristics is difficult to reliably discern in the temporal waveform, somewhat clearer visually in the STFT plots, and clearly reflected in the interpulse interval in the QPT signals.

Applying the method to each S1 during expiration in all the recorded data we obtained consistent results, as illustrated for 3 20s epochs in Fig. 2. Here the horizontal

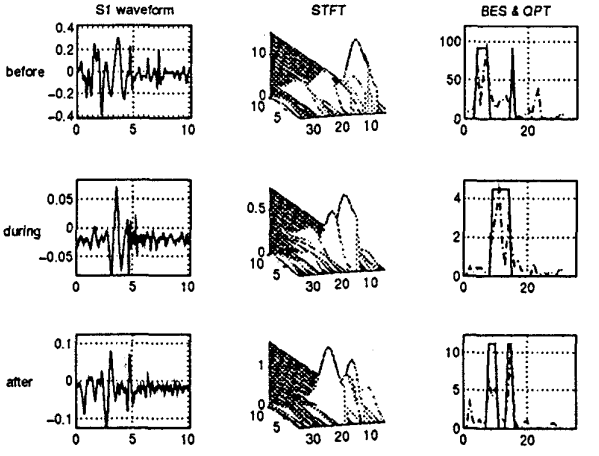

Figure 1: S1 Waveform, STFT results and BES/QPT of S1 sounds. The first row was before, the middle row during, and the bottom row after the hypovolemic episode.

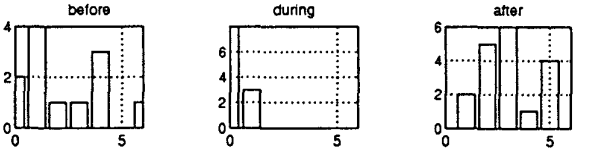

Figure 2: Histogram of the interpulse interval distribution of all expiration S1 sounds during 20 s epochs before, during, and after the hypovolemic episode.

axis is the interpulse interval length (in the index l) and the height of each bar represents the count of interpulse intervals of the corresponding length in that epoch. We note that the two normovolemic epochs shown show a wide distribution of interpulse intervals while the hypovolemic epoch contains only very short (0 or 1 interval) intervals.

Discussion and Conclusion: Testing on inspiratory S1 sounds in the same data set revealed no clear change with hypovolemia, as we had hypothesized. It appears from this preliminary study that the STFT may provide us with a tool to objectively observe the extent of splitting of S1 heart sounds. The interpulse interval statistic seems promising as a discriminator of the hypovolemic state. In addition, we noticed the clear presence of a small but perhaps significant number of S4 sounds during expiration during normovolemia but not during hypovolemia. The presence of the S4 sound can easily be seen in the QPT signal. Our current plan is to collect more extensive data and peform statistical tests of the discriminatory power of this interpulse interval statistic.

4. REFERENCES

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